Remote Sensing of Environment 81 (2002) 36–44

Remote Sensing of Environment

www.elsevier.com/locate/rse

Using a land cover classification based on satellite imagery to improve the precision of forest inventory area estimates

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Received 6 March 2001; received in revised form 6 September 2001; accepted 15 September 2001

Abstract

Estimates of forest area were obtained for the states of Indiana, Iowa, Minnesota, and Missouri in the United States using stratified analyses and observations from forest inventory plots measured in federal fiscal year 1999. Strata were created by aggregating the land cover classes of the National Land Cover Data (NLCD), and strata weights were calculated as proportions of strata pixel counts. The analyses focused on improving the precision of unbiased forest area estimates and included evaluation of the correspondence between forest/nonforest aggregations of the NLCD classes and observed attributes of forest inventory plots, evaluation of the utility of the NLCD as a stratification tool, and estimation of the effects on precision of image registration and plot location errors. The results indicate that the combination of NLCD-based stratification of inventory plots and stratified analyses increases the precision of forest area estimates and that the estimates are only slightly adversely affected by image registration and plot location errors.

1. Introduction

The Forest Inventory and Analysis (FIA) program of the Forest Service, U.S. Department of Agriculture, has the responsibility for periodically estimating and reporting the extent and volume of the timber resources of the United States. To comply with its federal mandate, the FIA program estimates extent through measures of forest area and estimates volume as the product of area and volume per unit area estimates. The forest area estimates are obtained using a combination of plot and remotely sensed data, while the volume per unit area estimates are obtained by measuring an extensive network of permanent field plots.

One estimate of forest area reported by FIA is forestland area. The FIA definition of forestland includes commercial timberland, some pastured land with trees, forest plantations, unproductive forested land, and reserved, noncommercial forested land. In addition, forestland must satisfy minimum stocking levels, a 0.405-ha (1 acre) minimum area, and a minimum cumulative crown width of 36.58 m (120 ft) and, therefore, excludes lands such as wooded strips, idle farmland with trees, and narrow windbreaks. FA is estimated as the product of total area and mean proportion forestland observed on FIA plots.

The combination of natural variability and budgetary constraints prohibits measurement of a sufficient number of plots to satisfy precision standards for estimates of most inventory variables unless the estimation process is enhanced using ancillary data. Traditionally, FIA has used aerial photography and a two-phased approach incorporating double sampling for stratification to increase the precision of inventory estimates (Hansen, 1990; Loetsch & Haller, 1964). In the first phase, an array of points or photo plots on the aerial photographs is interpreted and stratified using ocular methods, with the number of photo plots assigned to strata used as proportional estimates of stratum areas. In the second phase, field crews visit plots located at a subset of the locations of the photo plots and obtain observations of plot attributes. Using data obtained from this double-sampling approach and stratified estimation techniques (Cochran, 1977), regional estimates of forest land area and the precision of the estimates are calculated.

2. Satellite imagery

The FIA program has sought alternatives to aerial photographs as means of increasing the precision of forest area

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0034-4257/01/$ – see front matter
PII: S0034-4257(02)00330-3

estimates: (1) visual interpretation of the photographs is labor intensive and often subjective; (2) the quality and currency of the photographs are often inadequate; (3) the photographs may be expensive to purchase; (4) the photographs are cumbersome to acquire, transfer, handle, and store; and (5) consistent quality of interpretation with respect to photo plots associated or not associated with field plots is difficult to ensure. Increasingly, satellite imagery is being viewed as an alternative to aerial photographs. The primary advantages of this alternative are its digital format, border-to-border coverage, and consistency.

As a means of increasing the efficiency and precision of forest inventory estimation, satellite imagery has been used with two approaches, regression and stratification. With the regression approach, observations of a forest attribute obtained from inventory plots and the spectral values of pixels corresponding to these plots provide the basis for regression models. The models are used to predict the value of the attribute for all pixels in the area of interest, thus producing a predicted distribution of the attribute. Area-wide inventory estimates are obtained by summing or averaging over the pixel-based predictions. Knowledge of the spatial distribution of the spectral values of the pixels allows a predicted map of the spatial distribution of the forest attribute to be obtained also. In an estimation context, the map is a by-product, although for other applications, the map itself may be of primary interest, perhaps for identifying forested locations with particular characteristics. Considerable international attention has been devoted to the development and use of regression models for mapping and describing relationships between spectral values of satellite images and a variety of forest attributes: hardwood and conifer cover in Oregon, USA (Maiersperger, Cohen, & Ganio, 2001); height and basal area in Scotland (Puhr & Donoghue, 2000); biomass in Brazil (Steininger, 2000); volume in British Columbia, Canada (Gemmell, 1995); age and structure in the Pacific Northwest of the USA (Cohen, Spies, & Fiorella., 1995); age in Estonia (Nilson & Peterson, 1994); age in Colorado, USA (Nel, Wessman, & Veblen, 1994); biomass in England (Danson & Curran, 1993); and volume in New Brunswick, Canada (Ahern, Erdle, MacLean, & Kneppeck, 1991). Although developed for other purposes, these models and maps may be used to predict distributions of forest attributes of interest with the regression approach. Deppe (1998) investigated use of the regression approach to enhance estimation for forest area in Brazil and Bolivia, while Trotter, Dymond, and Goulding (1997) did likewise for volume in New Zealand. An increasingly popular variation of the regression approach uses nearest-neighbors techniques in lieu of regression models (e.g., Franco-Lopez, Ek, & Bauer, 2001; McRoberts, Franco-Lopez, Ek, & Bauer, 2000; Tokola, 2000; Tokola, Pitkanen, Partinen, & Muinonen, 1996; Tomppo, 1991; Trotter et al., 1997). Two disadvantages of the regression and nearest-neighbors approaches are foremost: First, bias in the inventory estimates may result if bias in the regression models or nearest-neighbors techniques produce biased predictions of the distribution of the forest attribute; and second, the resources necessary to obtain and register the satellite imagery and to develop the models or nearest-neighbors relationships may be substantial.

The stratification approach, sometimes characterized as the direct expansion method, eliminates these disadvantages, albeit with possibly less gain in precision. With this approach, the satellite image is used to stratify the area of interest by aggregating the area's associated satellite image pixels into homogeneous classes or strata. Values of inventory variables obtained from plots assigned to the same strata are also expected to exhibit a degree of homogeneity. If the stratification is accomplished prior to sampling and the within-stratum variances are known, then maximum precision may be achieved by designing the within-stratum sampling intensity to be proportional to the within-stratum variance. If the sampling intensity is independent of the stratification, then considerable increase in precision may still be achieved simply by using stratified analyses. Poso, Hame, and Paananen (1984) and Poso, Paananen, and Simila (1987) used the stratification approach with unsupervised classifications to increase the precision of inventory estimates of volume and age in Finland. The advantages of the stratification approach over the regression and nearest-neighbors approaches are that no resources are necessary to develop the models or nearest-neighbors relationships and, consequently, one potential source of bias in the inventory estimates is eliminated.

Despite their advantages, satellite images may still be expensive to obtain, register, and classify, even when used only for stratification. However, image classifications and/or maps do not necessarily need to be tailored to the specific application in order to produce a precision increase for inventory estimates. Hansen and Wendt (2000) used the existing GAP classification (National Council of the Paper Industry for Air and Stream Improvement [NCASI], 1996) to increase the precision of inventory estimates of volume and forest area for Indiana and Illinois, USA, thus eliminating the necessity of obtaining, registering, and classifying the imagery.

A second large-scale classification, the National Land Cover Data (NLCD), a digital product of the Multi-Resolution Land Characterization (MRLC) Consortium (Loveland & Shaw, 1996), is a land cover map of the conterminous United States consisting of assignment of each 30×30-m pixel to 1 of 21 land cover classes. The land cover classification was produced by the U.S. Geological Survey and was based on nominal 1992 Landsat 5 Thematic Mapper (TM) satellite imagery and a variety of ancillary data. Vogelmann et al. (2001) provide an excellent overview and discussion of the NLCD. Numerous appealing attributes of the NLCD make it an attractive alternative to aerial photography: (1) digital format; (2) free and immediate acquisition online (http://www.epa.gov/mrlc/nlcd.html); (3) consistency; (4) no user image registration or classification requirements; (5) elimination of much of the labor-intensive and subjective first phase of the double-sampling procedure, because stratum weights may be obtained from simple pixel counts; and (6) the border-to-border image coverage of a state instead of photo points that constitute only a sample. However, because the NLCD was not specifically designed as a means of stratification for forest inventory estimation, the correspondence of its classes to values of inventory variables and its utility for increasing precision require evaluation.

The objectives of the study focused on evaluating the NLCD as a stratification tool for improving the precision of FA estimates and were threefold: (1) to evaluate the correspondence between the NLCD classes and plot attributes observed by field crews; (2) to evaluate the utility of the NLCD as a stratification tool; and (3) to estimate the effects of uncertainty in the registration of the imagery underlying the NLCD and uncertainty in plot locations on the precision of FA estimates.

3. Data

Estimates of total FA for the states of Indiana (IN), Iowa (IA), Minnesota (MN), and Missouri (MO) in the North Central region of the United States were calculated using field observations of proportion forestland for FIA plots measured in federal fiscal year 1999 (FY99: October 1, 1998–September 30, 1999). Under the FIA program's annual inventory system (McRoberts, 1999), plots are established in permanent locations using a systematic sampling design. For each state, the plots measured in a single federal fiscal year comprise one of five 20% panels of plots selected for annual measurement on a rotating basis. Annually, each plot represents 12,014 ha (approximately 30,000 acres), while in aggregate, over a 5-year cycle, each plot represents 2403 ha (slightly less than 6000 acres). Calculations of area per plot indicate the annual target of 12,014 ha was approximately satisfied for these states for FY99 (Table 1).

Each FIA field plot consists of four 7.31-m (24 ft) radius circular subplots. These subplots are configured as a central subplot and three peripheral subplots with centers located at 36.58 m (120 ft) and azimuths of 0°, 120°, and 240° from the center of the central subplot. Among the observations field crews obtain are the proportions of subplot areas that satisfy specific ground land use conditions. A plot-level estimate of proportion forestland is obtained by aggregating proportions of several of these ground land use conditions over the four subplots and attributing the aggregated proportions to the plot as a whole. In addition, for this study, each plot was assigned to the NLCD land cover class associated with the pixel containing the center of the central subplot.

Table 1
Statewide sample characteristics

Statistic	State IN	IA	MN	MO
Total area (10^6 ha)	9.43	14.57	22.50	18.05
Plots measured in FY99	769	1223	1802	1504
Hectares/plot (target = 12,014)	11,913	12,262	12,473	12,001

4. Estimation

Because FIA uses a systematic sampling design with permanent ground plots, maximizing the precision of estimates via stratified random sampling is not an option. Nevertheless, considerable increase in precision can still be realized using stratified analyses if an effective stratification can be implemented, albeit independently of the sample selection. When using a systematic sampling design and satellite imagery for stratification, estimates of forest land area, FA, and associated estimates of variance, Var(FA), may be obtained using formulae for stratified analyses (Cochran, 1977):

$$\mathrm{FA} = A\sum_{j=1}^{J} W_j \hat{P}_j \tag{1}$$

and

$$\mathrm{Var(FA)} = A^2 \sum_{j=1}^{J} W_j^2 \hat{\sigma}_j^2 / n_j, \tag{2}$$

where A is total area; $j = 1, \ldots, J$ denotes stratum; W_j is the weight for the jth stratum calculated as the ratio of the number of pixels assigned to the jth stratum and the total number of pixels for all strata; $\hat{P}_j$ denotes the mean proportion forestland for plots assigned to the jth stratum; $\hat{\sigma}_j^2$ is the within-stratum variance for the jth stratum calculated as

$$\hat{\sigma}_j^2 = \frac{1}{n_j - 1}\sum_{i=1}^{n_j}(P_{ij} - \hat{P}_j)^2; \tag{3}$$

P_{ij} is the proportion forestland observed by the field crew for the ith plot in the jth stratum; and n_j is the number of plots assigned to the jth stratum. Variance estimates obtained using Eq. (2) ignore the slight effects due to finite population correction factors and to variable rather than fixed numbers of plots per stratum. Two initial strata, forest and nonforest, were created by aggregating the 21 NLCD land cover classes on the basis of their conformity to categories of ground land use conditions that FIA defines as forestland.

Precision estimates for forest area reported by the Forest Service are scaled to compensate for varying sample sizes associated with varying area sizes using a reference standard of 404,694 ha (1 million acres) (USDA Forest Service [USDA-FS], 1970). The scaled precision estimate, denoted as PREC for this study, is defined as

$$\mathrm{PREC} = \frac{[\mathrm{Var(FA)}]^{1/2}}{\mathrm{FA}}\left[\frac{\mathrm{FA}}{404,694}\right]^{1/2}, \tag{4}$$

where FA is expressed in hectares. The values of PREC obtained from Eq. (4) were divided by the square root of 5 to reflect values that would be expected following complete measurement of all five panels of plots over 5 years.

5. Methods

Investigations were conducted in three general areas: (1) an assessment of the correspondence between the NLCD-based forest and nonforest strata and plot attributes observed by field crews; (2) an investigation of the stratification utility of the forest and nonforest strata obtained by aggregating the NLCD land cover classes; and (3) and an assessment of the effects of image registration and plot location errors on the precision of forest land area estimates.

5.1. Correspondence between NLCD-based strata and field observations

Although strata used for improving precision need not correspond to familiar, well-defined classes, strata related to the FIA definition of forestland were expected to have greater utility for this application. Thus, the NLCD land cover classes selected for aggregation to form the forest stratum were those that were expected to conform most closely to the FIA definition of forestland. Nevertheless, the correspondence between the aggregation of NLCD land cover classes and the condition classes of the FIA plots is not expected to be exact. First, the NLCD classification was based on a sensing of land cover, while the FIA condition classes are based on land use and productivity observed by field crews and exclude some lands with tree cover. Second, the NLCD classification assigns each pixel to a single class, while FIA summarizes the attributes of four FIA subplots falling in three to four different pixels in terms of plot-level proportions for multiple ground land use conditions. Third, although the spectral attributes associated with a given pixel may be affected by attributes of adjacent pixels, these effects probably do not encompass 0.405 ha (1 acre) as is required for land to be considered FIA forestland.

Despite the expected imperfect correspondence between the NLCD land cover classes and the FIA condition classes, the NLCD may still be an effective means of stratification. An initial assessment of this potential was obtained using a crude measure of the correspondence between two forest/nonforest classifications of each plot: (1) the classification on the basis of whether the NLCD land cover class of the pixel containing the center of the center subplot was aggregated into the forest or nonforest stratum; and (2) the classification on the basis of whether the proportion forestland for the plot observed by the field crew satisfied a minimum proportion forestland threshold value necessary for the entire plot to be designated forestland. Although a threshold value is necessary for this analysis, such values are not prescribed by FIA, and the selection of any such value is necessarily arbitrary. Therefore, for proportion forestland thresholds ranging from 0.10 to 1.00, the correspondence between the two forest/nonforest classifications was evaluated using graphs of the proportion of plots correctly classified versus the proportion forestland threshold values.

5.2. Stratification

As a means of improving the utility of the stratification, the NLCD-based forest and nonforest strata were modified with respect to three factors: (1) the particular NLCD classes aggregated into the forest stratum; (2) reassignment of isolated groups of small numbers of pixels to conform to the forest or nonforest stratum in which they were embedded; and (3) separation of edge strata of varying widths from the forest and nonforest strata at forest/nonforest boundaries.

Two groupings of NLCD classes were investigated for aggregation into the forest stratum. The first grouping included NLCD Classes 33 (transitional),[1] 41 (deciduous forest), 42 (evergreen forest), 43 (mixed forest), 51 (shrubland), and 91 (woody wetland) in the forest stratum and is designated the total forest aggregation, because the forest stratum included all NLCD classes that might be considered forested classes. All other NLCD classes were grouped into the nonforest stratum. The second grouping included only NLCD Classes 41, 42, and 43 in the forest stratum and is designated the pure forest aggregation, because the forest stratum included only the NLCD classes that were known to be forested. Analyses with the pure forest aggregation were conducted only for IN and MN.

A clumping and sieving algorithm (ERDAS, 1997) was used to reassign pixels in isolated groups of small numbers of contiguous forest pixels to the nonforest stratum and pixels in isolated groups of small numbers of contiguous nonforest pixels to the forest stratum. Clumping and sieving was done to remove isolated groups of less than four pixels because of the approximate correspondence in area of four pixels (3600 m^2) to 0.4047 ha (4047 m^2), the minimum area necessary to be designated FIA forestland. Additional investigations were conducted with no pixel reassignments and with reassignments of isolated groups of eight pixels or fewer, approximately 0.810 ha (2 acres).

As a means of improving the precision of the proportion forestland estimates, three levels of stratification were

[1] The correct numerical designation for the transitional class is 33; its designation as 31 in Vogelmann et al. (2001) is attributed to a manuscript error (Vogelmann, EROS Data Center, U.S. Geological Survey, personal communication, 10 October 2001).

considered: one stratum (i.e., no stratification), two strata, and four strata. With a single stratum, the FIA plot data were analyzed as if they had been obtained using simple random sampling. Precision estimates obtained with this level of stratification are used for comparison purposes only. For the two-stratum approach, the forest and nonforest strata obtained by aggregating NLCD classes were used. For the four-stratum approach, two additional strata were created by subdividing the forest stratum into forest and forest edge and by subdividing the nonforest stratum into nonforest and nonforest edge (Hansen & Wendt, 2000). These edge strata were created by reassigning pixels in the original forest and nonforest strata based on their distance from a forest/nonforest boundary. Four distances or edge widths were investigated: one, two, three, and four pixels. Thus, for a two-pixel distance, pixels in the original forest stratum within two pixels of a nonforest pixel were reassigned to the forest edge stratum, while pixels in the original nonforest stratum within two pixels of a forest pixel were reassigned to the nonforest edge stratum. For IA, a forest edge stratum was not separated from the forest stratum because of the small number of forested plots.

The rationale for creating the additional strata is based on the knowledge that stratification with a systematic sampling design contributes to increasing precision under two conditions: (1) when within-stratum variances are smaller than the overall variance and (2) when strata with large variances represent relatively small proportions of the total population. For this application, plots located in the interior of the forest stratum and away from forest/nonforest boundaries are expected to be predominantly forest, while plots located in the nonforest stratum away from the forest/nonforest boundaries are expected to be predominantly nonforest. In both cases, within-stratum variances are expected to be relatively small, thus satisfying the first condition for which stratification reduces variance estimates. Plots located in an edge stratum, i.e., near forest/nonforest boundaries, are expected to exhibit greater variances due to a mix of forest and nonforest conditions on the plots and due to the greater probability of errors in assigning plots to strata. Nevertheless, the stratification is also expected to concentrate these erroneously stratified and mixed forest/nonforest plots into strata that represent relatively small proportions of the total area, thus satisfying the second condition for which stratification produces reductions in variance estimates.

Detailed analyses of the utility of the stratification were conducted for the total forest aggregation for all four states, for all levels of clumping and sieving, for all levels of stratification, and for all edge widths for the four-stratum approach. Similar analyses were conducted for the pure forest aggregation, but only for IN and MN, only for four-pixel clumping and sieving, and only for two-pixel edge widths when the four-stratum approach was used.

The effects of clumping and sieving were compared with respect to the precision of estimates, but only for the total forest aggregation. However, because of the intensive processing requirements that would be necessary to create edges around all isolated groups of small numbers of pixels, no edge strata were created in the absence of clumping and sieving. Thus, for the one-stratum (no stratification) approach, the effects of all three levels of clumping and sieving were compared; for the two-stratum approach, the effects of all three levels of clumping and sieving were again compared; but for the four-stratum approach, only the effects of the four- and eight-pixel levels of clumping and sieving were compared.

5.3. Location errors

The effects of image registration errors and plot location errors on the precision of proportion forestland estimates for the four-stratum approach with two-pixel edge widths were approximated using simulations. The precision of image registration is usually assessed using the root mean square error (RMSE) where errors are defined as differences between the known locations of ground control points and the locations of the same points on the image after registration. Registration precisions corresponding to RMSE values of one half pixel are usually deemed acceptable. Thus, the magnitude of the image registration error was simulated with a Gaussian distribution with zero mean and standard deviation of 15 m (half the width of a 30-m square pixel), but restricted to fall within 0.0–2.5 standard deviations. The direction of the error was simulated using a uniform distribution with range 0–359.99°.

A study by the USDA Forest Service to evaluate the bias and precision of GPS receivers reported that for receivers of the kind used by FIA field crews, average errors were approximately 7.9 m with maximum errors of approximately 20 m (Jasumback, 1996). Thus, the magnitude of the plot location error was simulated using a Gaussian distribution with zero mean and standard deviation 8.0 m, but restricted to fall within 0–2.5 standard deviations. The direction of the plot location error was simulated using a uniform distribution with range 0–359.99°. The resulting distribution of simulated plot location errors was concentric around zero with decreasing spatial density as the magnitude of the error increased (Fig. 1).

The effects of image registration and plot location errors on PREC were approximated using the following five-step Monte Carlo simulation procedure.

(1) *Image registration error*. A simulated image registration error was generated by randomly selecting magnitudes and directions from the distributions previously described. The location of each pixel in the NLCD was offset by this same random registration error.

(2) *Plot location error*. A simulated plot location error was generated for each plot by randomly selecting magnitudes and directions from the distributions previously described. The location of each FIA plot center was offset by a random location error generated individually for the plot.

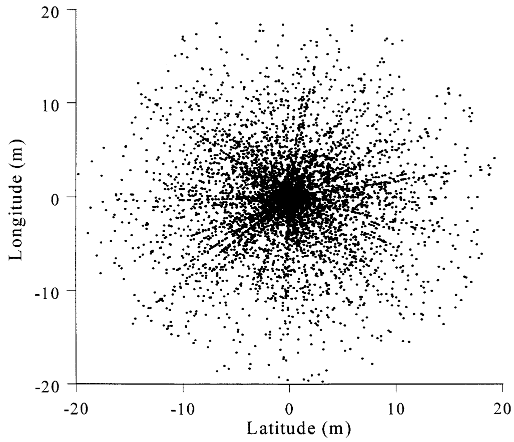

Fig. 1. Distribution of simulated plot location errors.

(3) *Stratification.* The FIA plots were restratified by assigning each plot to the stratum of the NCLD pixel with center (with image registration error) nearest the plot center (with location error).

(4) *Estimation.* Statewide estimates of FA and the variances of the FA estimates were obtained for the four-stratum approach with two-pixel edge widths using Eqs. (1)–(3). For each state, PREC was calculated using Eq. (4).

(5) *Repetition.* Steps 1–4 were repeated 1000 times to generate distributions of PREC estimates for comparison with the PREC values obtained from the original data.

6. Results

6.1. Correspondence between NLCD-based strata and field observations

Graphs of the proportion of plots correctly classified versus the proportion forestland threshold values indicated that for the total forest aggregation and four-pixel clumping and sieving, the greatest proportions correctly classified for MN and MO, the two relatively heavily forested states, ranged from 0.85 to 0.91 and were obtained for threshold values of 0.2–0.5, while the greatest proportions correctly classified for IN and IA, the two relatively sparsely forested states, ranged from 0.92 to 0.95 and were obtained for threshold values of 0.5–0.8 (Fig. 2). For no clumping and sieving, the graphs were similar, but the proportions correctly classified were slightly lower, while for eight-pixel clumping and sieving, the graphs were also similar, but the proportions correctly classified were slightly higher. For the pure forest aggregation with four-pixel clumping and sieving, the graphs were similar in shape to those for the total forest aggregation, although proportions correctly classified were slightly lower for IN and much lower for MN, the only two states considered. Overall, the proportions correctly classified were similar to results reported by Rack (in press) and Riemann, Hoppus, and Lister (2000). These results indicate that aggregations of NLCD classes into forest and nonforest strata have excellent potential to function as an effective means of stratification and that positive results accruing from stratifications based on these aggregations may be attributed to this strong correspondence rather than to spurious or random effects.

6.2. Stratification utility

For the total forest aggregation, four-pixel clumping and sieving, and a two-pixel edge width, the within-stratum estimates indicate that the objectives of stratification are achieved (Table 2a and b). For the two-stratum approach, the within-stratum standard errors were either smaller than overall standard errors as represented by the estimates for the approach with no stratification, or the weights assigned to strata with larger standard errors were smaller. For the four-stratum approach, the forest and nonforest within-stratum standard errors were smaller than the corresponding two standard errors, and the weights for the more variable edge strata were much smaller than the weights for the forest and nonforest strata from which they had been separated. The overall standard errors obtained for the two-stratum approach were smaller than those obtained without stratification, while the overall standard errors for the four-stratum approach were smaller than those obtained with the two-stratum approach.

A comparison of the total and pure forest aggregations with respect to their effects on the utility of the stratification was restricted to IN and MN, four-pixel clumping and sieving, and two-pixel edge widths when the four-stratum approach was used. For IN, the two aggregations produced

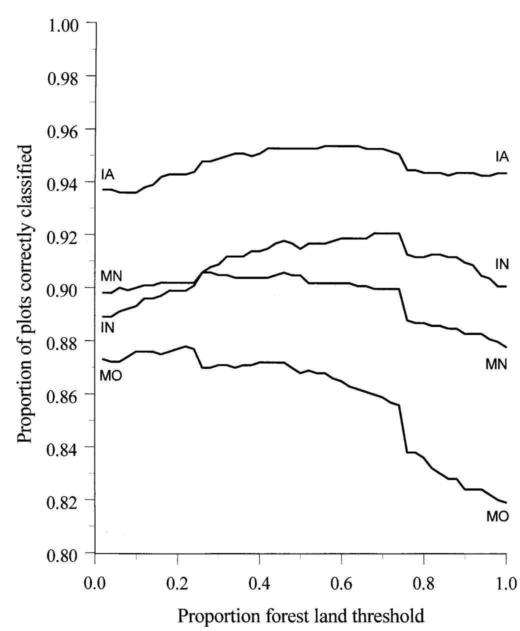

Fig. 2. Correspondence between NLCD-based forest and nonforest strata and proportion forest land observed by field crews.

Table 2

(a) Estimates for proportion forest land for forest stratum consisting of NLCD Classes 31, 41, 42, 43, 51, and 91[a]

	IN			IA			MN			MO		
Stratum	W_j	$\hat{P}_j$	$\left(\frac{\hat{\sigma}_j^2}{n_j}\right)^{0.5}$	W_j	$\hat{P}_j$	$\left(\frac{\hat{\sigma}_j^2}{n_j}\right)^{0.5}$	W_j	$\hat{P}_j$	$\left(\frac{\hat{\sigma}_j^2}{n_j}\right)^{0.5}$	W_j	$\hat{P}_j$	$\left(\frac{\hat{\sigma}_j^2}{n_j}\right)^{0.5}$
One-stratum (no stratification)												
All[b]	1.0000	0.1716	0.0127	1.0000	0.0552	0.0059	1.0000	0.2914	0.0104	1.0000	0.3312	0.0114
Two-stratum												
Nonforest	0.8010	0.0463	0.0070	0.9176	0.0166	0.0030	0.6516	0.0369	0.0049	0.6152	0.0568	0.0067
Forest	0.1990	0.7153	0.0338	0.0824	0.5139	0.0452	0.3484	0.7733	0.0156	0.3848	0.7355	0.0158
All[b]	1.0000	0.1794	0.0088	1.0000	0.0575	0.0046	1.0000	0.2935	0.0063	1.0000	0.3180	0.0074
Four-stratum with two-pixel edge width												
Nonforest	0.6546	0.0080	0.0028	0.8128	0.0018	0.0011	0.5377	0.0067	0.0021	0.4183	0.0078	0.0032
Nonforest edge	0.1465	0.2112	0.0311	0.1048	0.1258	0.0218	0.1139	0.1607	0.0216	0.1969	0.1693	0.0193
Forest edge	0.1060	0.5701	0.0502	–	–	–	0.0991	0.5587	0.0343	0.1533	0.5125	0.0274
Forest	0.0930	0.8905	0.0323	0.0824	0.5139	0.0452	0.2493	0.8541	0.0156	0.2315	0.8800	0.0149
All[b]	1.0000	0.1795	0.0078	1.0000	0.0570	0.0045	1.0000	0.2902	0.0058	1.0000	0.3189	0.0068

(b) Estimates for proportion forest land for forest stratum consisting of NLCD Classes 41, 42, and 43[a]

	IN			MN		
Stratum	W_j	$\hat{P}_j$	$\left(\frac{\hat{\sigma}_j^2}{n_j}\right)^{0.5}$	W_j	$\hat{P}_j$	$\left(\frac{\hat{\sigma}_j^2}{n_j}\right)^{0.5}$
One-stratum (no stratification)						
All[b]	1.0000	0.1716	0.0127	1.0000	0.2909	0.0104
Two-stratum						
Nonforest	0.8188	0.0552	0.0075	0.7885	0.1528	0.0091
Forest edge	0.1812	0.7324	0.0340	0.2115	0.8370	0.0175
All[b]	1.0000	0.1754	0.0087	1.0000	0.2975	0.0081
Four-stratum with two-pixel edge widths						
Nonforest	0.6746	0.0086	0.0032	0.6446	0.1007	0.0086
Nonforest edge	0.1442	0.2939	0.0323	0.1440	0.3664	0.0269
Forest edge	0.1000	0.6119	0.0489	0.1179	0.7401	0.0281
Forest	0.0811	0.9023	0.0334	0.0936	0.9540	0.0139
All[b]	1.0000	0.1747	0.0076	1.0000	0.2942	0.0076

[a] Four-pixel clumping and sieving.
[b] Estimates over all strata.

similar results, but for MN the total forest aggregation produced greater precision (Table 2a and b). For MN, shifting NLCD Classes 33, 51, and 91 from the forest to the nonforest stratum had several detrimental effects. First, as expected, combined weights for the nonforest and nonforest edge strata increased, and the within-stratum means of proportion forest-land increased for all strata. In addition, within-stratum standard errors increased substantially for the nonforest and nonforest edge strata, while they decreased for the forest and forest-edge strata. Because weights for the nonforested strata were greater than for the forested strata, the combined effects of increasing weights and increasing within-stratum standard errors for the nonforest strata produced greater overall standard errors for both the two- and four-stratum approaches. The effects on PREC were similar to those for the within-stratum estimates. For IN, the differences in PREC were small for the two aggregations, but for MN, they were relatively large. When NLCD Classes 33, 51, and 91 for MN were shifted to the nonforest stratum, PREC increased from 0.0389 to 0.0495 for the two-stratum approach and from 0.0362 to 0.0470 for the four-stratum approach with two-pixel edge widths, both with four-pixel clumping and sieving. These detrimental effects are attributed to the observation that substantial areas of forestland in MN are in wet, lowland areas and indicate that care must be exercised in selecting NLCD classes to aggregate into the forest and nonforest strata.

The effects on PREC of increasing levels of stratification were generally beneficial for all levels of clumping and sieving (Table 3). The effects of stratification may be assessed in terms of relative efficiency, the factor by which sample sizes would have to be increased to achieve the same precision without stratification. Because PREC is proportional to $n^{-1/2}$, where n is sample size, relative efficiencies may be calculated as the square of the ratio of PREC for the levels of stratification being compared. Relative efficiencies for no stratification and for the two-stratum approach ranged from 1.68 to 2.71, meaning that samples sizes would have to be increased by 68% to 171% to achieve the same precision without stratification. Relative efficiencies for no stratification and the four-stratum approach with optimal edge widths ranged from 1.78 to 3.93, meaning that sample sizes would have to be increased by 78 to 293% to achieve the same precision without stratification. The magnitudes of these relative efficiencies indicate that the NLCD has considerable utility as a means of stratification; i.e., the effort to obtain the NLCD classification, to complete the clumping and sieving operation, to select and aggregate the classes into forest and nonforest strata, and to create the edge classes is justified in terms of the realized gain in precision.

Given the four-stratum approach, i.e., that edges were at least one pixel in width, the effects on PREC of increasing edge widths were not great. Minimum values of PREC were usually achieved for either one- or two-pixel edge widths for both four- and eight-pixel clumping and sieving, while PREC values for 4-pixel edge widths were generally greater than for smaller edge widths.

The effects of clumping and sieving on PREC were also not great. For IA, MN, and MO, PREC values corresponding to optimal edge widths were slightly smaller for eight-pixel clumping and sieving, although for IN, the smallest PREC value was achieved for four-pixel clumping and sieving. However, the differences in PREC for the optimal edge widths for four- and eight-pixel clumping and sieving were relatively small.

6.3. Effects of location errors

The simulations showed that the combined effects of simulated image registration errors and plot locations errors were only slightly detrimental (Table 4). These combined effects caused the center of the central subplot to change pixel locations for approximately 15% of plots, regardless of the state. However, a change of pixel location did not necessarily result in a change in stratum assignment. For the four-stratum approach with two-pixel edge widths, the proportion of plots that changed stratum assignments was less than 0.025 for all strata in all states. For all four states, the values of PREC calculated from the original data were smaller than and exterior to the central 95% of the simulated distributions, indicating that the impacts of the location errors were detrimental and statistically significant. Nevertheless, the absolute magnitudes of differences between the original PREC values and the medians of the simulated distributions were not great.

Table 3
Effects of stratification on PREC (Eq. (4))[a]

		PREC			
Number of strata	Edge width	IN	IA	MN	MO
No clumping and sieving					
1	0	0.0663	0.0671	0.0642	0.0595
2	0	0.0465	0.0540	0.0390	0.0403
Four-pixel clumping and sieving					
1	0	0.0662	0.0670	0.0641	0.0593
2	0	0.0447	0.0517	0.0382	0.0390
4	1	0.0334	0.0515	0.0362	0.0355
4	2	0.0400	0.0502	0.0362	0.0358
4	3	0.0414	0.0509	0.0364	0.0352
4	4	0.0419	0.0515	0.0371	0.0361
Eight-pixel clumping and sieving					
1	0	0.0663	0.0671	0.0642	0.0595
2	0	0.0438	0.0501	0.0379	0.0386
4	1	0.0369	0.0503	0.0358	0.0358
4	2	0.0415	0.0488	0.0358	0.0315
4	3	0.0419	0.0503	0.0358	0.0349
4	4	0.0420	0.0561	0.0359	0.0360

[a] Forest stratum: NLCD Classes 31, 41, 42, 43, 51, 91.

Table 4
Effects of locations errors on PREC (Eq. (4))[a]

	PREC			
	IN	IA	MN	MO
No location errors	0.0400	0.0502	0.0362	0.0358
With simulated location errors				
0.025 percentile	0.0416	0.0540	0.0379	0.0367
Median	0.0430	0.0592	0.0386	0.0374
0.975 percentile	0.0442	0.0663	0.0393	0.0380

[a] Forest stratum: NLCD classes 31, 41, 43, 51, 91; 4-pixel clumping and sieving; 4-strata with 2-pixel edge width.

7. Conclusions

Four conclusions may be drawn from the study: (1) The high levels of correspondence between the forest and nonforest strata obtained by aggregating NLCD land cover classes and plot attributes observed by field crews indicate that stratification benefits obtained by using aggregations of the NLCD classes may be attributed to real relationships, not simply spurious or random effects. (2) The NLCD provides an effective means of stratification when its classes are aggregated into forest and nonforest strata. (3) The separation of forest and nonforest edge strata from the original forest and nonforest strata enhances the effectiveness of the stratification. (4) The effects of image registration errors and plot locations errors on the precision of forest area estimates are slightly detrimental, although the overall impacts are nearly negligible. In addition, the inclusion of NLCD Classes 33, 51, and 91 in the forest stratum improved the precision of estimates for MN, a state with considerable forestland in wet, lowland areas, but not for IN. The effects of varying edge widths when separating the forest and nonforest edge strata were not great, although one to two pixel edge widths were usually optimal, while four-pixel widths were generally less than optimal. The effects of clumping and sieving on precision were also not great.

A general recommendation is to construct strata as follows: aggregate NLCD Classes 33, 41, 42, 43, 51, and

91 into the forest stratum; use four-pixel clumping and sieving to conform approximately to the FIA requirement that forestland must comprise at least 0.405 ha; and create at least four strata (nonforest, nonforest edge, forest, forest edge) using two-pixel widths for edge strata. The general conclusion is that the use of proportion forestland observed on FIA plots in conjunction with the NLCD as a stratification tool and stratified analyses is an effective method for obtaining statewide forest land area estimates.

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